Estimating Direct Rebound Effects for Personal Automotive Travel in Great Britain

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Estimating direct rebound effects for personal automotive travel in Great Britain

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Abstract

Direct rebound effects result from increased consumption of cheaper energy services. For example, more fuel-efficient cars encourage more car travel. This study is the first to quantify this effect for personal automotive travel in Great Britain. We use aggregate time-series data on transport activity, fuel consumption and other relevant variables over the period 1970-2011 and estimate the direct rebound effect from the elasticity of both vehicle and passenger kilometres with respect to: a) vehicle fuel efficiency (km/MJ); b) the fuel cost of driving (£/km); and c) road fuel prices (£/MJ). We estimate a total of 108 models, paying careful attention to methodological issues and model diagnostics. Taking changes in fuel efficiency as the explanatory variable, we find little evidence of a long-run direct rebound effect in Great Britain over this period. However, taking changes in either the fuel cost of driving or fuel prices as the explanatory variable we estimate a direct rebound effect in the range 9% to 36% with a mean of ~19%. This estimate is consistent with the results of US studies and suggests that around one fifth of the potential fuel savings from improved car fuel efficiency may have been eroded through increased driving. We also show how the normalisation of distance travelled (per capita, per adult or per driver) affects the results obtained.

Key words

JEL codes

Highlights

- We estimate the direct rebound effect for car travel in Great Britain to be around 19%.

- We obtain significant results for price elasticities, but not for efficiency elasticities.

- Estimates are lower when distance travelled is normalised to the number of drivers

- We find little relationship between the estimated rebound and model robustness

1. Introduction

Direct rebound effects relate to increased consumption of energy services whose effective price has fallen as a consequence of improved energy efficiency. For example, we expect more fuel-efficient cars to encourage more car travel, thereby offsetting some of the potential energy savings. The magnitude of such effects may vary widely between different energy services, between different social groups and over time, with long-term rebounds being of greatest interest for public policy (Sorrell, 2007). Compared to the majority of energy services, the direct rebound effect for personal automotive transport is relatively well-studied since data on vehicle travel and fuel consumption are routinely collected by national and regional authorities. However, the evidence to date is overwhelmingly dominated by studies from the US (Greene, 2012; Hymel et al., 2010; Sorrell, 2007). Since road fuel prices, vehicle efficiencies and population densities are comparatively low in the US, while car ownership and usage are comparatively high, US results may not provide a reliable guideline for other countries.

For econometric studies, the most obvious measure of the direct rebound effect is the elasticity of demand for the relevant energy service (S) with respect to some measure of energy efficiency (ε): $\eta_\varepsilon(S) = \partial \ln(S) / \partial \ln \varepsilon$. For example, the energy service provided by private cars may be measured in vehicle kilometres (vkm), their fuel consumption (E) in megajoules (MJ) and their fuel efficiency ($\varepsilon = S/E$) in km/MJ. As shown by Sorrell and Dimitropoulos (2007a), the elasticity of demand for fuel with respect to fuel efficiency ($\eta_\varepsilon(E)$) is then given by:

$$\eta_\varepsilon(E) = \eta_\varepsilon(S) - 1 \qquad\qquad 1$$

If $\eta_\varepsilon(S)$ is zero, an x% improvement in fuel efficiency should lead to an x% reduction in fuel consumption ($\eta_\varepsilon(E) = -1$). But since improved fuel efficiency makes driving cheaper, some of the potential fuel savings may be 'taken back' through increased distance travelled ($\eta_\varepsilon(S) \geq 0$ and $\eta_\varepsilon(E) \geq -1$). This may result from greater use of vehicles and/or induced increases in the vehicle stock which in turn may be associated with (induced) changes in land use patterns, public transport provision and other variables that encourage greater car dependence. In practice, however, reliable data may not be available on vehicle fuel efficiency, or the limited variation in fuel efficiency in the available data sets may preclude robust inference. Hence, a more common approach is to estimate the direct rebound effect from one of three *price* elasticities, namely:

$\eta_{p_S}(S)$: the elasticity of demand for vehicle kilometres with respect to the fuel cost per kilometre (p_S);

$\eta_{p_E}(S)$: the elasticity of demand for vehicle kilometres with respect to the price of fuel (p_E); or

$\eta_{p_E}(E)$: the elasticity of demand for fuel with respect to the price of fuel.

Where: $p_S = p_E/\varepsilon$. Estimates of price elasticities may be more precise than estimates of efficiency elasticities if there is greater variation in the relevant explanatory variables. But the first two of these elasticities ($\eta_{p_S}(S)$) and $\eta_{p_E}(S)$) can only be considered equivalent to the efficiency elasticity ($\eta_\varepsilon(S)$) if fuel prices are exogenous, the demand for vehicle kilometres depends solely on the fuel price per kilometre, and consumers respond in the same way to improvements in fuel efficiency as they do to reductions in fuel prices (Sorrell and Dimitropoulos, 2007a). While the first of these assumptions is reasonable, the second and third are less so (Sorrell and Dimitropoulos, 2007a). For $\eta_{p_E}(E)$ to be equivalent to $\eta_\varepsilon(S)$ we need the additional assumption that fuel efficiency is constant - which is problematic for a study of rebound effects (Frondel and Vance, 2013). If fuel efficiency is instead influenced by fuel prices ($\varepsilon = f(p_E)$), the following inequality should hold (Sorrell and Dimitropoulos, 2007a):

$$\left|\eta_{p_E}(S)\right| \le \left|\eta_{p_S}(S)\right| \le \left|\eta_{p_E}(E)\right| \qquad 2$$

If fuel efficiency depends upon fuel prices, then fuel efficiency is endogenous. Moreover, there may be other reasons why fuel efficiency is endogenous. For example, if drivers expect to travel long distances they may be more likely to choose a fuel-efficient car, thereby creating an additional positive correlation between vehicle kilometres and fuel efficiency that may bias estimates of the rebound effect (Small and Van Dender, 2005). Possible responses to this include finding suitable instrumental variables for fuel efficiency or estimating a simultaneous equation model that includes separate equations for the number of cars, the total distance travelled and the fuel efficiency of the car fleet. But adequate instruments can be difficult, if not impossible, to find (Murray, 2006) and lack of data may preclude the estimation of a full structural model. In view of this, Frondel and Vance (2013) recommend

using $\eta_{p_E}(S)$ as the 'best' measure of the direct rebound effect since fuel prices are more likely to be exogenous.

These difficulties have led to a variety of approaches to estimating the direct rebound effect for personal automotive transport, with most studies basing their estimates on the elasticity of vehicle kilometres with respect to the fuel cost per kilometre ($\eta_{p_S}(S)$). Sorrell *et al* (2009) reviewed 17 of these studies, including seven using aggregate time-series and cross-sectional data, four using aggregate panel data and five using household survey data. All but one of these studies applied to the US. Despite wide differences in specifications and methodologies, most estimated the long-run direct rebound effect to lie in the range 10-30%.

Perhaps the most rigorous study was by Small and van Dender (2007; 2005) who used panel data from US states over the period 1961-2001. Small and van Dender estimated a simultaneous equation model that allowed $\eta_{p_S}(S)$ to be derived, as well as a variant that allowed $\eta_\varepsilon(S)$ to be estimated. The variant performed relatively poorly, with the estimate of $\eta_\varepsilon(S)$ being small and statistically insignificant. Hence, Small and van Dender based their conclusions on their estimates of $\eta_{p_S}(S)$ - which suggested a long-run direct rebound effect of ~22%. More recently, Greene (2012) investigated the direct rebound effect for US transport over a similar time period, but using national time-series data instead. Similar to Small and van Dender, Greene failed to obtain a statistically significant estimate of $\eta_\varepsilon(S)$. However, his estimates of $\eta_{p_E}(S)$ suggested a long-run rebound effect of ~23% - virtually identical to Small and Van Dender. Greene also tested and rejected the hypothesis that $\eta_{p_E}(S) = -\eta_\varepsilon(S)$ - thereby raising doubts about the validity of $\eta_{p_S}(S)$ as a measure of the direct rebound effect.

In summary, while an efficiency elasticity ($\eta_\varepsilon(S)$) may be the *preferred* measure of the direct rebound effect for personal automotive transport, most studies have either been unable to estimate this elasticity or have found the relevant coefficient to be statistically insignificant. In contrast, many studies have used one or more price elasticities ($\eta_{p_E}(S), \eta_{P_S}(S)$ or $\eta_{p_E}(E)$) as *alternative* measures of the direct rebound effect for personal automotive transport and have commonly obtained statistically significant results. The reasons for these differences are unclear, but may be linked to the endogeneity of fuel efficiency, the limited variation of fuel efficiency in the available data sets and/or because consumers respond differently to changes

in fuel prices than to changes in fuel efficiency - perhaps because fuel efficiency is correlated with other attributes of the energy service provided by private cars. While the absence of significant estimates of $\eta_\varepsilon(S)$ suggests the long-run direct rebound effect is close to zero, the multiple estimates of price elasticities suggest that the long-run direct rebound effect lies in the range 10-30%. These contradictory findings suggest the need for caution in interpreting the results of such studies.

Since the publication of the review by Sorrell (2007), the literature on rebound effects has grown considerably. However, most of the estimates for personal automotive transport are broadly in line with the above findings (Greene, 2012; Hymel and Small, 2015; Hymel et al., 2010; Su, 2012, 2015). Notable exceptions include Frondel *et al* (2007; 2012) who find much larger rebound effects for car travel in Germany and Linn (2013) who finds the same for the US. Linn's study is also unique in obtaining statistically significant estimates of $\eta_\varepsilon(S)$ and in finding these to be larger than his estimates of $\eta_{p_E}(S)$. This may be because Linn is able to control for two potential sources of bias, namely: the correlation between fuel efficiency and other vehicle attributes; and the interdependence of distance travelled among vehicles in multivehicle households. Recent US literature has also indicated that the direct rebound effect may fall over time as incomes rise and as car ownership and use approaches saturation levels (Hughes et al., 2008; Hymel et al., 2010; Small and Van Dender, 2007). All these studies use either aggregate panel data from US states or detailed micro-data on car ownership and use by individual households and the large number of observations in these datasets allows the specification of structural models that provide more precise parameter estimates.

This paper builds upon this literature by providing the first estimate of the direct rebound effect for personal automotive travel in Great Britain, and by investigating how the choice of model specification and elasticity measure affects the results obtained. We use aggregate time-series data on car use and fuel consumption over the period 1970-2011 and choose Great Britain (GB) rather than the UK since the required data is not available for Northern Ireland. We develop a number of models with different specifications and use these to estimate and compare three different measures of the long-run direct rebound effect, namely $\eta_\varepsilon(S)$, $\eta_{p_S}(S)$ and $\eta_{p_E}(S)$. In addition, we measure distance travelled (S) in two different ways (vehicle kilometres and passenger kilometres) and explore how different normalisations of these variables influence the results. Our approach pays careful attention to evaluating and comparing the statistical robustness of the estimated models.

2. Methodology

Our approach involves estimating a total of **108 models**, each of which falls into one of **12 Groups** – listed in Table 1 We first estimate two **base models** within each Group – one of which is a *static* specification and the second a *dynamic* specification. We then explore a number of **variants** of those models and use a series of **robustness tests** to choose the 'best performing' models.

Below we explain in turn the definition of model Groups, the specification of base models, the specification of model variants and the robustness tests.

Model Groups

The model Groups are defined by the choice of explanatory variable (vehicle or passenger kilometres), the normalisation of that explanatory variable (per capita, per adult or per licensed driver) and the specification of the fuel costs of driving (Type A or Type B) (see Table 1). We explain each of these choices in turn.

Table 1 Classification of model groups

Group	Explained variable	Normalisation of explained variable	Specification of the fuel cost of driving
1	VKM	Per capita	Type A - p_E and ε
2	VKM	Per adult	Type A - p_E and ε
3	VKM	Per driver	Type A - p_E and ε
4	VKM	Per capita	Type B - p_S
5	VKM	Per adult	Type B - p_S
6	VKM	Per driver	Type B - p_S
7	PKM	Per capita	Type A - p_E and ε
8	PKM	Per adult	Type A - p_E and ε
9	PKM	Per driver	Type A - p_E and ε
10	PKM	Per capita	Type B - p_S
11	PKM	Per adult	Type B - p_S
12	PKM	Per driver	Type B - p_S

Choice of explanatory variable

Most previous studies have defined the energy service provided by personal automotive vehicles (*S*) as the annual distance travelled by those vehicles - measured in vehicle kilometres (VKM). But an equally valid alternative is to measure the energy service in passenger kilometres (PKM) and thereby allow for changes in average vehicle load factor. Cheaper driving (e.g. through improved fuel efficiency) may potentially lead to less lift sharing, higher car ownership, more vehicle kilometres and hence more fuel use with little change in passenger kilometres. Estimates of rebound effects may therefore depend upon how the energy service is defined. To investigate this, we estimate models using both VKM and PKM as the explained variable and compare the results obtained[1].

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[1] Technical improvements in fuel economy (e.g. better aerodynamics) may also influence producer and consumer decisions on the average power and weight of new cars (measured, for example by tonne kilometres) - thereby creating another route for rebound effects to appear (Ajanovic et al., 2012). We do not address these complexities here, but we note that the average power and weight of new vehicles in the EU has been on upward trend for decades.

Normalisation of explanatory variable

Previous studies have not been consistent in their specification of distance travelled (S), either measuring it in absolute terms or normalising it to population, the number of adults or the number of licensed drivers (Sorrell and Dimitropoulos, 2007b). Changes in the age structure of the population, the propensity of young people to learn to drive and/or the proportion of female drivers will have different effects on the explained variable depending upon the normalisation used - thereby influencing the coefficients of the relevant models. For example, if the proportion of licensed drivers in the population is increasing, then normalising distance travelled to population may lead to a higher estimate of income elasticity than normalising to the number of drivers. To investigate this, we estimate and compare models using *all three* normalisations.

Specification of the fuel costs of driving

We also investigate two ways of specifying the fuel cost of driving which we term Type A and Type B.

- **Type A models** include retail fuel prices (p_E) and fleet average fuel efficiency (ε) as *separate* explanatory variables, thereby allowing $\eta_{p_E}(S)$ and $\eta_\varepsilon(S)$ to be estimated.

- **Type B models** combine fuel prices and fuel efficiency into a *single* explanatory variable, the fuel cost of driving ($p_S = p_E / \varepsilon$), thereby allowing $\eta_{p_S}(S)$ to be estimated.

Type B models impose the hypothesis that the response to improved fuel efficiency is identical to the response to lower fuel prices, while *Type A* models allow this hypothesis to be tested. By estimating both types, we can compare the results obtained.

Base models

In common with most studies in this area, we specify the annual distance travelled (S_t) by personal automotive vehicles in Great Britain as a function of real equivalised household income (Y) and the real fuel cost of driving - whether specified in the Type A (p_E and ε) or Type B ($p_S = p_E / \varepsilon$) forms. We also include a proxy variable for the level of congestion (C) on GB roads, together with a dummy variable (X) that is non-zero in years when there was an oil price shock. Using only four variables is appropriate given our limited number of observations.

In each model Group we estimate **base models** using both *static* and *dynamic* specifications. The former specify distance travelled as a function of the explanatory values in the same time period – thereby implicitly assuming that the observed demand is in equilibrium. But since responses to efficiency improvements and fuel price changes take time, this type of model may not adequately capture the long-run adjustments in which we are interested. Hence we also investigate dynamic models in which distance travelled is specified as a function of historic values of the explained variables. To conserve degrees of freedom we use a 'partial adjustment' specification which simply adds a one period lag of the explained variable. In both cases we choose the standard double log (constant elasticity) formulation.

The static and dynamic versions of each model type are then as follows:

Type A static:

$$\ln S_t = \beta_0^{AS} + \beta_1^{AS} \ln Y_t + \beta_2^{AS} \ln p_{E_t} - \beta_3^{AS} \ln \varepsilon_t + \beta_4^{AS} X_t + \beta_5^{AS} C_t + u_t^{AS} \qquad 3$$

Type A dynamic:

$$\ln S_t = \beta_0^{AD} + \beta_1^{AD} \ln Y_t + \beta_2^{AD} \ln p_{E_t} - \beta_3^{AD} \ln \varepsilon_t + \beta_4^{AD} X_t + \beta_5^{AD} C_t + \beta_6^{AD} S_{t-1} + u_t^{AD} \quad 4$$

Type B static:

$$\ln S_t = \beta_0^{BS} + \beta_1^{BS} \ln Y_t + \beta_2^{BS} \ln p_{S_t} + \beta_3^{BS} X_t + \beta_4^{BS} C_t + u_t^{AS} \qquad 5$$

Type B dynamic:

$$\ln S_t = \beta_0^{BD} + \beta_1^{BD} \ln Y_t + \beta_2^{BD} \ln p_{S_t} + \beta_3^{BD} X_t + \beta_4^{BD} C_t + \beta_5^{BD} S_{t-1} + u_t^{BD} \qquad 6$$

Where S_t is vehicle or passenger kilometres travelled by the personal automotive fleet in Great Britain (GB) in year t, p_{E_t} is average fuel prices (£/MJ), ε_t is fleet average fuel efficiency (vkm/MJ), p_{S_t} is fuel costs per vehicle kilometre (£/vkm), Y_t is mean equivalised per capita income, X_t is a dummy variable for the oil price shock years of 1974 and 1979, C_t is a proxy measure for road congestion and u_t is the error term.

For illustration, the long-run elasticity of distance travelled with respect to the fuel cost of driving ($\eta_{p_S}(S)$) is given by β_2^{BS} in the static Type B model (Equation 5) and

$(\beta_2^{BD} / (1 - \beta_5^{BD}))$ in the dynamic version (Equation 6). In the latter, β_2^{BD} is the short-run elasticity and β_5^{BD} measures the speed of adjustment.

We form our proxy measure of congestion (C_t) by dividing the normalising variable for the explained variable (i.e. population, number of adults or number of licensed drivers) by the total road length in GB in that year. This is a crude approach, but data on congestion in GB is of poor quality and actual congestion is likely to be endogenous (Hymel et al, 2010; Small and Van Dender, 2005). Alternative methods for measuring congestion are discussed in Su (2010). We form our fuel consumption variable (E_t) by summing gasoline and diesel consumption by cars (in MJ)[2] and our fuel price variable (p_{E_t}) by weighting the price of each by their share of total car fuel consumption. This aggregation is necessary because our data on distance travelled does not distinguish between gasoline and diesel cars. In practice, diesel cars tend to be more fuel-efficient, larger and more powerful than gasoline cars, as well as being more intensively used (Schipper and Fulton, 2009, 2013).[3] The proportion of diesel cars in the GB fleet grew rapidly after 1990, and by 2011 diesel accounted for ~40% of total GB car fuel consumption.

Model variants

Starting with one static and one dynamic model in each of 12 Groups we arrive at 24 base models. These are then *re-specified* in four ways as described below:

Quadratic income variants

First, we investigate the addition of a **quadratic** term for log equivalised per capita income ($\ln Y_t$) to allow for the possibility of a 'peaking' relationship between income and distance travelled. Such a relationship is suggested by our data (Figures 1 and 2) and is consistent with the broader evidence on 'peak car' which suggests that distance travelled has begun to decline in several OECD countries (Kuhnimhof et al., 2013; Metz, 2013). For illustration, the Type B static model becomes:

$$\ln S_t = \beta_0^{BS} + \beta_1^{BS} \ln Y_t + \beta_2^{BS} (\ln Y_t)^2 + \beta_3^{BS} \ln p_{S_t} + \beta_4^{BS} X_t + \beta_5^{BS} C_t + u_t^{AS} \qquad 7$$

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[2] Since the volumetric energy density of gasoline is ~90% that of diesel, aggregating fuel consumption on an energy basis will lead to slightly different results than aggregating on a volumetric (or weight) basis. This is a minor concern for US studies since the majority of cars use gasoline. But the choice is more important for EU studies since diesel cars from a significant proportion of the fleet.

[3] An increasing proportion of diesel cars may therefore be associated with higher fleet average fuel efficiency and greater distance travelled. Diesel has also benefited from favourable tax treatment in the past (although no longer), creating the possibility of a further association with average fuel prices. This is a potential source of endogeneity bias, but lack of data on the proportion of diesel vehicles precludes a straightforward solution.

The level of equivalised per capita income at which distance travelled starts to fall (Y_p) is then given by:

$$Y_p = \exp\left[\frac{-\beta_1^{BS}}{2\beta_2^{BS}}\right]$$

8

And the long-run income elasticity of distance travelled is given by:

$$\eta_Y(S) = \beta_1^{BS} + 2\beta_2^{BS} \ln Y$$

9

The equivalent expression for this elasticity in the dynamic model is:

$$\eta_Y(S) = \frac{\left(\beta_1^{BD} + 2\beta_2^{BD} \ln Y\right)}{1 - \beta_5^{BD}}$$

10

Hence, in the quadratic variants, the income elasticity varies with the level of per capita income and becomes negative when $Y > Y_p$. In presenting the results below, we evaluate this elasticity at the mean value of $\ln Y$ in our dataset.

Asymmetric variants

Second, we investigate the possibility of *asymmetric* responses to changes in either fuel prices (p_E - Type A) or driving costs (p_S - Type B). Asymmetric responses to price changes have been widely observed in the literature (Dargay and Gately, 1997; Gately and Huntington, 2002) and are typically ascribed to a combination of induced technical change, irreversible investments, habits and/or the embodiment of higher efficiency standards in regulations (Frondel and Vance, 2013). Following Dargay (2007) and as used in later studies (e.g. Hymel and Small, 2015), our approach involves decomposing p_{E_t} (or p_{S_t}) as follows:

$$p_{E_t} = p_{E_1} + p_{E_t}^r + p_{E_t}^f$$

11

Where:

$$p_{E_t}^r = \sum_{t=2,T} \max\left[0, (p_{E_t} - p_{E_{t-1}})\right]$$

12

$$p_{E_t}^f = \sum_{t=2,T} \min\left[0, (p_{E_t} - p_{E_{t-1}})\right]$$

13

Where $p^r_{E_t}$ ($p^f_{E_t}$) represents the cumulative effects of all increases (decreases) in price since the start of the sample: Hence, $p^r_{E_t}$ is non-negative and non-decreasing, while $p^f_{E_t}$ is non-positive and non-increasing. It is the coefficient on the latter that is relevant to rebound effects, since falls in fuel prices reduce price per km in a similar manner to improvements in fuel efficiency.

Reduced variants

Third, we investigate eliminating variables that are found to be insignificant[4] in the above specifications and then re-estimating these ***reduced*** models. This approach prioritises parsimony. In practice, if the eliminated variables are co-linear they may be individually insignificant but jointly significant. Although we do not test for this, a test for multicollinearity forms one of our robustness checks.

Co-integrated variants

Finally we investigate the stationarity of the time series in our 'best fitting' static models. With time series data it is common for one or more of the variables to be non-stationary, creating the risk of spurious regressions.[5] While this may be avoided by differencing the data, this would prevent the estimation of long-run relationships. But it is possible for two or more non-stationary variables to be *co-integrated*, meaning that certain linear combinations of these variables are stationary and that there is a stable long-run relationship between them. Co-integration techniques allow these relationships to be identified. Hence, we also test the time series and residuals in the 'best performing' static models for unit roots and, if found, re-estimate these ***co-integrated*** models using relevant techniques.

Modelling sequence

This procedure leads us to estimate a total of **nine** models in each of the twelve groups, or **108 models in total**. Each group contains static and dynamic versions of the base, quadratic, asymmetric and reduced specifications, together with a single co-integrated specification. We estimate the co-integrated model with a specialised technique ('canonical co-integrating regression') and the remainder with OLS.

The procedure for selecting the models relies upon a comprehensive series of robustness tests that are described below. These tests are intended to be comprehensive in terms of the

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[4] Unless otherwise stated, the significance level in the reported results is 0.05 (5%).

[5] The mean and variance of a stationary process are constant over time and the covariance between two points depends only on the time distance between them and not the time period itself.

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behaviour of coefficients and residuals, stability, parsinomy and functional form. These tests are used to create an aggregate *robustness score* for each model which guides their selection at each stage. The procedure for selecting the model variants is as follows:

1. ***Base models***: We first estimate the base static and dynamic models in each of the twelve groups (using OLS) and evaluate the robustness of each using the tests illustrated in Table 2 (*24 models in total*).

2. ***Quadratic income variants***: We then add a quadratic term for log per capita income to each model and repeat the estimations and robustness tests. We compare the aggregate robustness score for each model in Stage 2 with the corresponding score for the model without the quadratic income term from Stage 1 and choose the best performing specification to take through to Stage 3 (*24 models in total*).

3. ***Asymmetric variants***: We take the best performing model (base or quadratic) and add terms to allow for asymmetric price responses. We then repeat the estimations and robustness tests and also apply a Wald test to identify whether asymmetry is present. We select the Stage 3 specification over the Stage 1 or 2 specifications if the former has a higher robustness score AND the Wald test is significant. If not, we continue with the Stage 1 or Stage 2 specification. The selected models are taken through to Stage 4 (*24 models in total*).

4. ***Reduced variants***: We take the selected models from Stage 3 and remove those coefficients which were found to be insignificant at the 5% level – thereby creating 'reduced' specifications. We then repeat the estimations and robustness tests. (*24 models in total*)

5. ***Co-integrated variants***: Finally, we examine the results of the last four stages and select the 'best performing' static models in each of the twelve groups on the basis of their robustness scores. For each of these we test the data and residuals for unit roots using a method proposed by Phillips and Perron (1988). If the variables are found to be co-integrated we re-estimate the model using a co-integration technique proposed by Park (1992). In practice, all 12 'best performing' models were found to be co-integrated[6] and hence all were re-estimated at this stage (*12 models in total*).

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[6] All variables in the best performing models (excluding the binary oil price shock variable) could not reject the null hypothesis of a unit root (i.e. non-stationarity) in levels form, but all variables rejected the null in first differences. In all cases, the residuals reject the null hypothesis of a unit root in levels form. However, we note that unit roots tests have relatively low power with the number of observations used here – making it more difficult to reject the null hypothesis of a unit root when coefficient values are in the region of 0.9. This reduces the level of confidence we can have in the existence of unit roots and co-integration.

Robustness tests

In the context of econometrics the term 'robust' or 'robustness' often refers to estimation strategies that alleviate one or a limited number of problems, such as outliers and non-normally distributed residuals (Andersen, 2008; Erceg-Hurn and Mirosevich, 2008). In these circumstances, it is better to clarify precisely what is being made robust - such as standard errors that are robust to heteroscedasticity (Stock and Watson, 2008). To capture a multi-dimensional concept of robustness, our preferred approach is to construct a composite indicator. Hence, to estimate the robustness of each model, we conduct a series of diagnostics tests and aggregate the results into an overall ***robustness score*** - with higher scores implying 'better' models. In Stages 1-4, we evaluate each static and dynamic model against *thirteen* different diagnostic tests that are summarised in Table 2. We score the performance of each model against each of these tests and construct a weighted sum of results to obtain an overall score which we express in percentage terms. We use two different weighting rules: the first based on our judgement of the 'relative importance' of each diagnostic test, and a second which gives equal weighting to each test (to avoid charges of subjectivity).

Some of these tests are not appropriate for co-integrated models, while others are not available for such models with our software (EViews). Hence, for the co-integrated models in Stage 5 we use a more limited set of *six* diagnostic tests summarised in Table 3. Tests for serial correlation and endogeneity are not included for the cointegrated models and there is some debate about whether our estimation technique ('canonical co-integrating regression') is immune to these (Kurozumi and Hayakawa, 2009; Montalvo, 1995; Park, 1992). CUSUM and CUSUM of squares are also not available for co-integrated models in EViews so instead we use a test that simultaneously identifies co-integrated time series and parameter stability (Hansen, 1992). Similarly, the three information criteria are not available, so we use a simple goodness of fit measure instead (R^2).

Table 2 Summary of robustness tests and weighting rules for the models in Stages 1-4

No.	Test	Description	Equal Weighting	Unequal Weighting
1	Coefficient signs	Do all statistically significant coefficients (p<0.05) have the expected signs? Score for yes.	2	1
2	Coefficient magnitudes	Do all statistically significant coefficients have plausible[7] magnitudes? Score for yes	2	1
3	Serial correlation	Lagrange multiplier[8] with two lags used to test for serial correlation of the residuals (Breusch and Pagan, 1979). Score for absence of serial correlation.	2	1
4	Heteroscedasticity	Lagrange multiplier used to test for heteroskedasticity of the residuals (Breusch and Pagan, 1979). Score for absence of heteroscedasticity	1	1
5	Normality	Lagrange multiplier used to test for normality of the residuals (Jarque and Bera, 1987). Score for normally distributed residuals.	1	1
6	Multicollinearity	Centred variance inflation factors[9] used to test for collinear variables. Score for absence of multicollinearity.	1	1
7	CUSUM	Cumulative sum of recursive residuals used to test for the stability of coefficient estimates over time (Brown et al., 1975). Score for residual stability	2	1
8	CUSUM of	Cumulative sum of recursive squared	2	1

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[7] Congestion elasticities greater than 2.0 and a lagged dependent variable greater than 0.8 were deemed to be implausible. No exclusions were deemed necessary for the other coefficients.

[8] Used in preference to Durbin-Watson test because the latter is only operationalised with one lag and is not applicable where lagged explained variables are included.

[9] The centered VIF is the ratio of the variance of the coefficient estimate from the original equation divided by the variance from a coefficient estimate from an equation with only that regressor and a constant. This provides a measure of how much the variance is increased because of co-linearity with other variables.

	squares	residuals used to test the. stability of coefficient estimates over time (Brown et al., 1975). Score for residual stability.		
9	Akaike information criterion	Akaike (1974) information criterion used to evaluate the trade-off between goodness of fit and model complexity in each model group.[10] Involves comparing and ranking the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
10	Hannan and Quinn information criterion	Hannan and Quinn (1979) information criterion used to evaluate the trade-off between goodness of fit and model complexity in each model group. Involves comparing and ranking the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
11	Schwarz information criterion	Schwarz (1978)information criterion used to evaluate the trade-off between goodness of fit and model complexity in each model group. Involves comparing and ranking the base, quadratic, asymmetric and reduced model variants in each group. Score 1 for rank 1, 0.5 for rank 2, 0.33 for rank 3 and 0 for rank 4.	Max of 1	Max of 1
12	RESET-1	Regression specification error test (RESET) used to determine whether inclusion of squares of explanatory variables (proxied by square of fitted	2	1

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[10] Models which are too complicated risk 'over-fitting' the data (Burnham and Anderson, 2002). Alternative tests, not applied here, are available which define parsimony in terms of the complexity of model functional form (Rissanen, 1987).

		values) significantly improves model fit (Ramsey, 1969). Score if no specification error indicated.		
13	RESET-2	Regression specification error test (RESET) used to determine whether inclusion of squares and cubes of explanatory variables (proxied by square and cube of fitted values) significantly improves model fit (Ramsey, 1969). Score if no specification error indicated.	2	1

Table 3 Summary of robustness tests and weighting rules for the co-integrated models (Stage 5)

No.	Name	Description	Equal Weighting	Unequal Weighting
1	Coefficient signs	Do all statistically significant coefficients (P<0.05) have the expected signs? Score for yes.	2	1
2	Coefficient magnitudes	Do all statistically significant coefficients have *plausible* magnitudes? Score for yes	2	1
3	Normality	Lagrange multiplier used to test for normality of the residuals (Jarque and Bera, 1987) Score for normally distributed residuals.	1	1
4	Multicollinearity	Centred variance inflation factors used to test for collinear variables. Score for absence of multicollinearity.	1	1
5	Stability	A test after Hansen (1969) used to test the stability of coefficient estimates over time. Score for passing this test.	2	1
6	R^2	Simple R^2 test used to evaluate goodness of fit. For equal (unequal) weighting, score 2 (1) if $R^2 > 0.95$ and score 1.75 (0.875) if $R^2 > 0.90$	2	1

3. Data

We take data on VKM and PKM in GB (S_t) over the period 1970-2011[11] from DTp (2013) and DTp (2010), and data on UK car fuel consumption (E_t) over the same period from DECC (2013a). Both time series include commercially rented vehicles (e.g. taxis) and company cars, since travel and fuel consumption by these groups are not independently identified.[12] We scale the DECC data in proportion to the GB share in UK population and use this to construct our aggregate fuel efficiency variable ($\varepsilon_t = S_t / E_t$). Schipper *et al* (1993) provides an insightful discussion of the uncertainties and potential biases with this type of approach, but

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[11] We excluded 2012 as household income data for that year was not available at the time the research was carried out.

[12] Changes in the tax treatment of company cars are likely to have influenced both new-car purchases and car usage patterns.

our data provides little alternative. We take nominal gasoline and diesel prices from DECC (2013b), convert these to 2011 prices with a 'before housing costs deflator' (Cribb et al., 2013) and construct an aggregate fuel price by weighting by the relative share of gasoline and diesel consumption in each year. Reflecting changes in fuel specifications, we use the price of 4* gasoline before 1989 and the price of 'premium unleaded' gasoline after that date (Bolton, 2013). We take data on mean equivalised real household income (Y_t) from IFS (2013), population data from the Office for National Statistics and data on licensed drivers and road length from DTp (2010, 2013). Where necessary, we use linear interpolation to adjust these data series to end of year values. The use of equivalised incomes adjusts for changes in average family size and composition.

Trends in each of these variables are illustrated in Figures 1-5. Both vehicle and passenger kilometres have approximately doubled since 1970, but the rate of growth slowed after the 1990 recession, subsequently plateaued and then declined (Figure 1 and 2). This pattern ('peak car') has been observed in several countries and typically predates the fall in per capita incomes that followed the 2008 financial crisis. This important trend appears to be driven by a number of factors that are only partly captured by the quadratic income and congestion variables in our specifications (Metz, 2013).

The average vehicle load factor (PKM/VKM) fell by 12% over this period, from 1.83 in 1970 to 1.61 in 2011 (Figure 3). The 'bump' in this time series in 1993 is an artefact of changes in the data collection methodology for VKM that occurred in that year, but the rate of decline of average load factor appears to have slowed after that date.

Fleet average on-road fuel efficiency has improved by ~67% since 1970 with most of these improvements occurring after 1980 (Figure 3). Retail fuel prices were volatile during the 1970s and have since been on an upward trend. The range of variation in these variables in GB over the last 40 years has been less than in the US owing to: first, the relatively higher efficiency of the GB vehicle fleet; second, the absence of fuel efficiency regulations in GB; and third, the much higher taxation of road fuels in GB (~60% of retail price) which dampens the impact of international oil price fluctuations. The fuel price trends since 1990 have increased the average fuel cost per kilometre while the fuel efficiency trends have reduced it, with the result that the real fuel cost per vehicle kilometre (p_S) has remained fairly constant since that date. Such factors are likely to make the estimation of rebound effects more difficult for GB than for the US, since there is less variation in the relevant explanatory variables.

Figure 4 shows that equivalised real per capita income doubled between 1970 and 2009, but fell slightly following the financial crisis. Road building has kept up with population growth throughout this period, but not with the growth in the number of drivers, leading to a 65% increase in the ratio of drivers to road length (~89 drivers per km in 2011). This is likely to have increased congestion, although factors such as the degree of urbanisation, traffic management and changes in the relative proportion and use of different types of roads will also affect congestion trends. The 'bump' in 1992 is probably due to methodological changes in the collection of data on road length in that year.

Figure 1 Trends in vehicle kilometres in Great Britain 1970-2011.
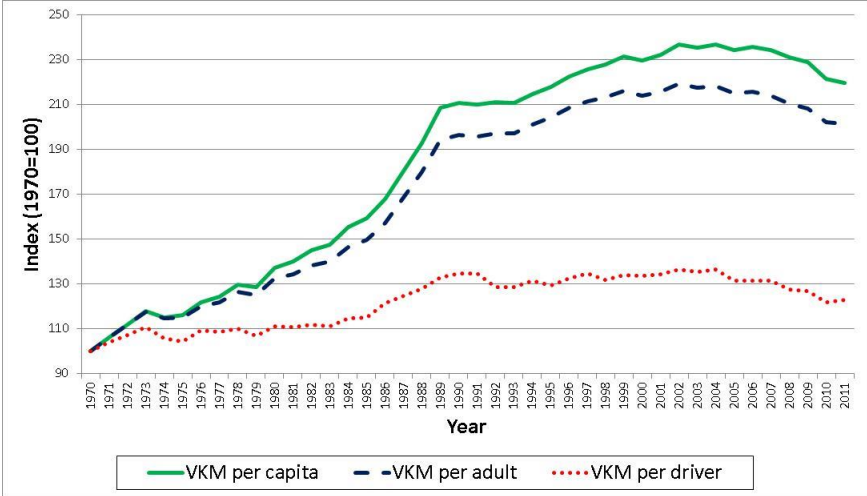

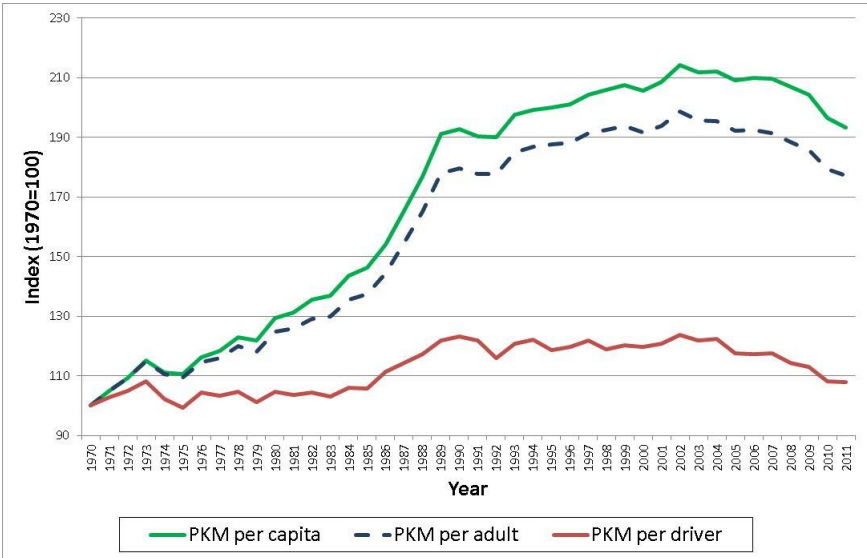*Figure 2 Trends in passenger kilometres in Great Britain 1970 – 2011*

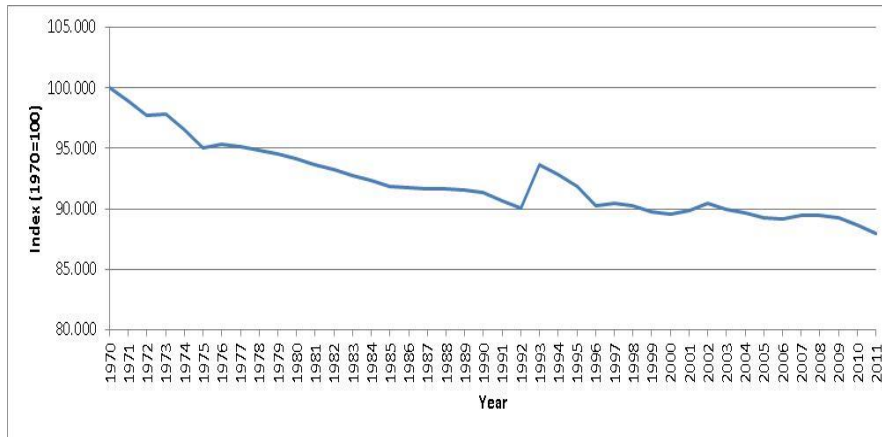*Figure 3 Trends in the average load factor of cars in Great Britain 1970-2011*

Figure 4 Trends in fuel intensity, real fuel prices and real fuel cost per kilometre for cars in Great Britain 1970-2011
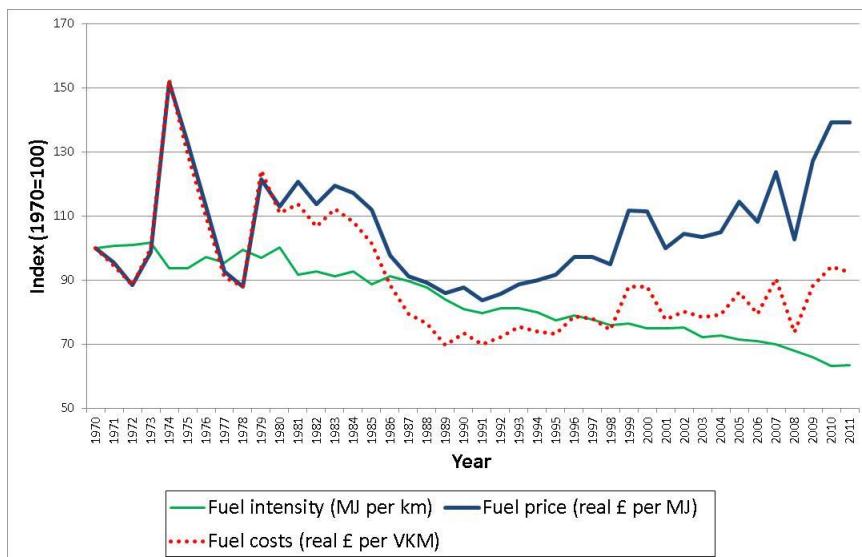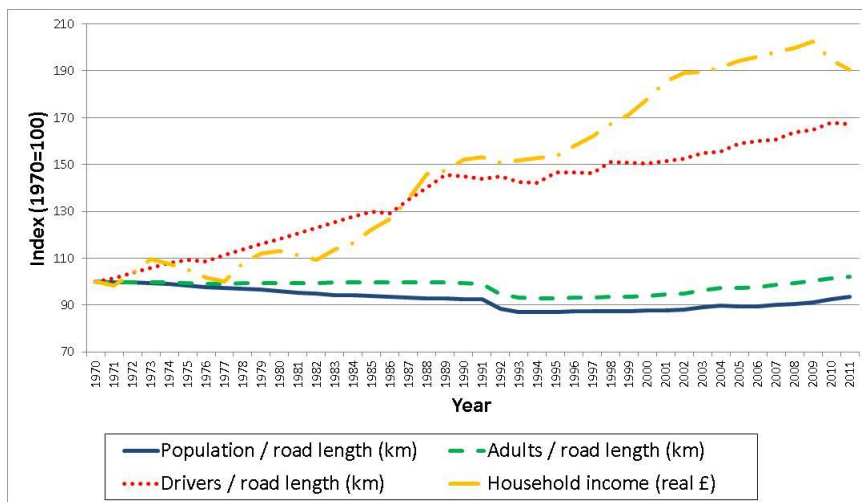

Figure 5 Trends in equivalised per capita income and three congestion proxies for Great Britain 1970-2011

4. Results

In this section we report and interpret the most relevant results from the 108 modelling runs, focussing upon statistically significant estimates of the relevant coefficients that have expected signs and plausible magnitudes (see footnote 7). Specifically, we report in turn: the coefficient estimates; the estimates of rebound effects; and the relationship between coefficient estimates and model robustness. Full details of the results are available from the authors.

Coefficient estimates

As Table 4 shows, 39 models produced statistically significant estimates of the long-run income elasticity of vehicle kilometres, while 43 produced comparable estimates for passenger kilometres. The results suggest that, on average, a 1% increase in equivalised per capita income was associated with a 0.51% (0.55%) increase in vehicle (passenger) kilometres over this period.[13] As expected, normalising distance travelled to the number of licensed drivers led to lower estimates of income elasticity, but there was little difference between the results for static, dynamic and co-integrating specifications. For comparison, a review of international studies by Goodwin et al. (2004) found a mean estimate for income elasticity of 0.5 from static models and 0.3 from dynamic models (both for vehicle kilometres), while a UK study by Dargay (2007) produced estimates in the range 0.95 to 1.12.

The quadratic specifications performed relatively well, with a total of 33 (35) models producing significant estimates of the level of income at which vehicle (passenger) kilometres began to fall. The mean for the former (£532/week) was slightly lower than the mean for the latter (£558/week),[14] with both being higher than the mean equivalised household income in 2003 - although this fell after 2008.

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[13] Estimates for vehicle kilometres range from 0.18 to 0.83, while those for passenger kilometres ranged from 0.28 to 1.09.

[14] Estimates for vehicle kilometres ranged from £457 to £639, while those for passenger kilometres ranged from £449 to £688.

Table 4 Mean estimates of the elasticity of distance travelled with respect to equivalised per capita income

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	0.57	0.57	0.39	0.51
	(12/18)	(13/18)	(14/18)	(39/54)
PKM	0.56	0.62	0.48	0.55
	(13/18)	(14/18)	(16/18)	(43/54)

Note Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

Table 5 indicates that 46 models produced statistically significant estimates of the long-run elasticity of distance travelled with respect to our proxy measures of 'congestion'.[15] These suggest that, on average, a 1% increase in these proxies was associated with a 1.25% (1.0%) reduction in vehicle (passenger) kilometres over this period. Although road length per driver changed significantly more than road length per person and per adult over this period (Figure 4), this coefficient was never significant in the vehicle kilometres models. However, this difference may result in part from the explained variable being normalised to the same measure as the congestion proxy in each model (i.e. people, adults or drivers). US studies (Hymel et al., 2010; Small and Van Dender, 2005) have yielded substantially smaller estimates for these proxies, but congestion is likely to be lower in the US since there is approximately three times more road space per driver.

Table 5 Mean estimates of the elasticity of distance travelled with respect to our proxy measures of congestion

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	-1.32	-1.19	N/A	-1.25
	(8/18)	(10/18)	(0/18)	(18/54)
PKM	-1.28	-1.18	-0.52	-1.0
	(9/18)	(10/18)	(9/18)	(28/54)

Note: Both the explained variable (vehicle or passenger kilometres) and road length are normalised to the same measure (population, adults or drivers). Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

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[15] Estimates for vehicle kilometres ranged from -1.47 to -0.85 while those for passenger kilometres ranged from -1.51 to -0.30.

A total of 40 models produced statistically significant estimates of the oil price shock coefficient. On average, these suggest that the 1974 and 1979 oil price shocks were associated with a contemporaneous 5.2% (4.6%) reduction in vehicle (passenger) kilometres.[16] Despite applying to GB, our mean estimate for this variable is close to recent estimates from the US (Greene, 2012; Hymel et al., 2010; Small and Van Dender, 2005).

The most important results are the coefficients relevant to rebound effects. These are summarised below.

Rebound estimates
Estimates of the direct rebound effect can be obtained from the coefficients on fuel efficiency (ε) or fuel prices (p_E) in the Type A models, or the coefficient on the fuel cost of driving (p_S) in the Type B models. We derive and summarise these estimates in two ways.

- First, we identify those estimates that were *statistically significant* (at the 0.05 level) with plausible magnitudes and signs. These estimates, along with their standard errors, are listed in Tables A.1 to A.4 (see Annex 1) in descending order of model robustness. We then calculate the *simple means* of those estimates which are presented in Table 7 and Table 9 below.

- Second, we take *all* the relevant estimates, whether or not they are statistically significant and/or appropriately signed, and calculate the *inverse variance weighted means* of those estimates. These results are presented in Tables 6, 8 and 10 below[17].

The second approach weights the estimate from each model in inverse proportion to its variance, leading to the lowest-variance estimate of the overall mean that is unbiased. For example, for fuel prices in the Type A static models, the relevant formula is:

$$\overline{\beta}_2^{AS} = \frac{\sum_i \beta_{2i}^{AS} / \mathrm{var}(\hat{\beta}_{2i}^{AS})}{\sum_i 1 / \mathrm{var}(\hat{\beta}_{2i}^{AS})} \qquad\qquad 14$$

Where *i* indexes over the relevant number of Type A static models. For the dynamic models, where the rebound estimates are given by ratio of coefficients (e.g. $\beta_2^{BD} / (1 - \beta_5^{BD})$), we use an approximation based upon the Delta Method (Benichou and Gail, 1989) to recover the relevant standard errors. The approach is summarised in Annex 2 and leads, for example, to

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[16] Estimates for vehicle kilometres ranged from -0.068 to -0.041, while those for passenger kilometres ranged from -0.062 to 0.033.

[17] We are grateful to an anonymous reviewer for suggesting we implement this methodology.

the following equation for the variance of the long-run rebound estimates in the Type B dynamic model:

$$\text{var}[\eta_{p_S}^{BD}(S)] \approx \left(\frac{1}{1-\overline{\beta}_5^{BD}}\right)^2 \text{var}(\beta_2^{BD}) + \left(\frac{\overline{\beta}_2^{BD}}{(1-\overline{\beta}_5^{BD})^2}\right)^2 (\beta_5^{BD}) + 2\left(\frac{\overline{\beta}_2^{BD}}{(1-\overline{\beta}_5^{BD})^3}\right) \text{cov}(\beta_2^{BD}, \beta_5^{BD}) \quad 15$$

Below we report our (significant and inverse-variance weighted) estimates of rebound effects based upon changes in fuel efficiency, fuel prices and fuel costs respectively.

Rebound estimates based upon fuel efficiency

Importantly, *none* of the Type A models provided a statistically significant estimate of the elasticity of vehicle or passenger kilometres with respect to fuel efficiency ($\eta_\varepsilon(S)$). In other words, using conventional statistical criteria, we find no evidence of a rebound effect in response to improvements in fuel efficiency.

Using the inverse-variance weighted results, we estimate a rebound effect of ~9% for vehicle kilometres and 10-15% for passenger kilometres (Table 6), but only when these are normalised to population or the number of adults. When distance travelled is normalised to the number of drivers, the mean estimate is not of the anticipated sign.

Taken together, *these results provide little evidence that improvements in fuel efficiency have led to an increase in distance travelled in GB over the last 40 years.* As noted earlier, two of the most rigorous US studies reached exactly the same conclusion (Greene, 2012; Small and Van Dender, 2005).

Table 6 Estimated rebound effects for fuel efficiency ($\eta_\varepsilon(E)$) - inverse variance weighted mean of all estimates

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	8.8%	8.7%	-10.9%	0.8%
PKM	15.2%	9.9%	-27.1%	-3.1%

Note Each table entry is the mean of the inverse variance weighted estimates in that category. These means are calculated using the results from <u>all</u> the relevant models, regardless of whether they were statistically significant or of the expected sign.

Rebound estimates based upon fuel prices

We find much stronger evidence that changes in fuel prices have led to changes in distance travelled ($\eta_{p_E}(S)$). As shown by Table 7, 41% (52%) of the Type A vehicle (passenger) kilometres models provided statistically significant estimates of $\eta_{p_E}(S)$. For vehicle kilometres, these results imply a long-run direct rebound effect in the range 10.6% to 22.2%,

with a mean of **17.2%**, while for passenger kilometres they imply a long-run direct rebound effect in the range 9.2% to 27.8%, with a mean of **17.4%**. In the latter case, the largest estimate came from the dynamic specification.

The inverse-variance weighted results are similar, with the estimates for both vehicle and passenger kilometres suggesting a slightly lower rebound effect of **15.2%** (Table 8). Hence, both sets of results suggest that the choice between vehicle or passenger kilometres has little influence on the estimated rebound effect. The invariance-weighted estimates are comparable to the statistically significant results when normalising distanced travelled to population or the number of drivers, but lower when normalising to the number of adults because of the relatively high variability associated with larger rebound estimates in these models.

A clear implication of these results is that normalising distance travelled to the number of drivers leads to lower estimates of the direct rebound effect. One possible interpretation is that lower driving costs encourage more people to gain licenses and purchase cars, as well as to drive those cars further. But to test this hypothesis properly we would need to estimate a full structural model.

Table 7 Estimated rebound effects for fuel prices ($\eta_{P_E}(S)$) – mean of statistically significant estimates

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	17.9%	20.5%	13.8%	17.2%
	(3/9)	(4/9)	(4/9)	(11/27)
PKM	17.7%	18.4%	15.8%	17.4%
	(5/9)	(5/9)	(4/9)	(14/27)

Note Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

Table 8 Estimated rebound effects for fuel prices ($\eta_{P_E}(S)$) - inverse variance weighted mean of all estimates

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	17.2%	16.8%	13.3%	15.2%
PKM	17.6%	12.9%	15.1%	15.2%

Note Each table entry is the mean of the inverse variance weighted estimates in that category. These means are calculated using the results from <u>all</u> the relevant models, regardless of whether they were statistically significant or of the expected sign.

Rebound estimates based upon fuel costs

Turning to the Type B models, we also find good evidence that changes in the fuel cost of driving ($p_S = p_E / \varepsilon$) have led to changes in distance travelled. As indicated in Table 9, 63% of the Type B vehicle kilometres models provided statistically significant estimates of $\eta_{p_S}(S)$ along with 85% of the passenger kilometres models (Tables A.3 and A.4). It is notable that more models provided significant estimates of $\eta_{P_S}(S)$ than $\eta_{P_E}(S)$, despite fuel prices varying more than the fuel cost of driving over the last 20 years (Figure 3).

The statistically significant results imply a long-run direct rebound effect in the range 10.9% to 26.8% for vehicle kilometres, with a mean of **18.7%.** The corresponding results for passenger kilometres are 13.4% to 36.3%, with a mean of **20.8%.** The invariance-weighted estimates are slightly lower, with means of **15.2%** and **17.7%** respectively. Again, normalising distance travelled to the number of drivers leads to lower estimates (~14%).

These estimates of the direct rebound effect based upon changes in the fuel cost of driving appear to be slightly larger than those based upon changes in fuel prices (Tables 7 and 8). In addition, the dynamic models tend to provide slightly larger significant estimates than the static models with means of 25.0% and 16.8% (23.1% and 19.0%) respectively for vehicle (passenger) kilometres. The largest estimate overall is provided by a dynamic model (36.3%).[18] Again, normalising distance travelled to the number of drivers leads to lower estimates.

Table 9 Estimated rebound effects for fuel cost per kilometre ($\eta_{P_S}(S)$) – mean of statistically significant estimates

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	18.8%	21.7%	14.4%	18.7%
	(5/9)	(7/9)	(5/9)	(17/27)
PKM	19.9%	23.4%	19.5%	20.8%
	(7/9)	(7/9)	(9/9)	(23/27)

Note Each table entry is the mean of the statistically significant estimates in that category, while the numbers in brackets indicate the fraction of models in each category that provided statistically significant estimates.

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[18] Using the statistically significant results, short-run estimates of $\eta_{P_S}(S)$ from the dynamic models range from 5.4% to 8.3% (mean of 6.8%) for vehicle kilometres while those for passenger kilometres range from 6.3% to 11.5% (mean of 8.9%).

Table 10 Estimated rebound effects for fuel cost per kilometre ($\eta_{P_S}(S)$) - inverse variance weighted mean of all estimates

	Per capita	**Per adult**	**Per driver**	**Mean**
VKM	15.0%	17.0%	14.2%	15.2%
PKM	16.9%	19.7%	14.8%	17.7%

Note Each table entry is the mean of the inverse variance weighted estimates in that category. These means are calculated using the results from <u>all</u> the relevant models, regardless of whether they were statistically significant or of the expected sign.

Summary of rebound estimates

In summary, *if* changes in fuel efficiency are taken as the appropriate explanatory variable ($\eta_\varepsilon(S)$), we find **little** evidence of a long-run direct rebound effect in GB over the last 40 years. However, if changes in either the fuel cost of driving ($\eta_{P_S}(S)$) or fuel prices ($\eta_{P_E}(S)$) are taken as the appropriate explanatory variable we find **good** evidence of a direct rebound effect, with most statistically significant estimates lying in the range **9% to 36%** with a mean of **~19%**. Using the inverse weighted mean of all estimates gives a slightly lower figure of **~16%** (Table 11).

One half of our Type A models provided significant estimates of $\eta_{P_E}(S)$ and three quarters of our Type B models provided significant estimates of $\eta_{P_S}(S)$. The estimates vary with the specification and measures used, but appear:

- slightly lower when distance travelled is normalised to the number of drivers rather than to the number of adults or people;

- slightly higher when rebound is estimated with respect to the fuel cost per kilometre, rather than fuel prices; and

- slightly higher when basing results upon statistically significant estimates, rather than the inverse-variance weighted mean of all estimates.

However, there is a significant overlap in the range of estimates for each specification and measure. We also observe that: a) the evidence for asymmetric responses to fuel price changes is relatively ambiguous, with the null hypothesis of no asymmetry being rejected in 10 of the 24 models where this was tested; and b) our robustness tests provide little grounds for choosing dynamic over static models, since the mean robustness score for the former (60%) is only marginally higher than that for the latter (57%).

Table 11 Summary of rebound estimates

Rebound measure	Simple mean of significant estimates	Invariance-weighted mean of all estimates
Fuel prices – VKM	17.2%	15.2%
Fuel prices – PKM	17.4%	15.2%
Fuel costs – VKM	18.7%	15.2%
Fuel costs – PKM	20.8%	17.7%
Average	18.5%	15.8%

Overall, our results are consistent with the majority of studies in this area, most of which apply to the US and measure the direct rebound effect from variations in fuel costs ($\eta_{P_S}(S)$).

Hence, the differences in population density, land use patterns, car ownership and other variables between the US and the UK do not appear to have a significant influence on the estimated direct rebound effect. However, as previously observed by Greene (2012) and Small and Van Dender (2005) amongst others, we find an important discrepancy between estimates of the direct rebound effect based upon efficiency elasticities and those based upon price elasticities. To explore this point further, we applied a Wald Test to 41 of the 54 Type A models to test the hypothesis (imposed in the Type B models) that the elasticity of distance travelled with respect to fuel prices was equal and opposite to the elasticity of distance travelled with respect to efficiency (i.e. $\eta_{P_E}(S) = -\eta_\varepsilon(S)$).[19] The results were ambiguous:

- The coefficients on the two variables were not found to be significantly different in 8 of the 20 VKM models (9 of the 21 PKM models), but in these cases the coefficient on fuel efficiency was always insignificant albeit mostly of the expected sign (namely in 6 of the 8 VKM models and 7 of the 9 PKM models).

- Conversely, the coefficients on the two variables were found to be statistically significantly different in the remaining models, but in these cases the coefficient on fuel efficiency was usually statistically significant but always the 'wrong' sign (implying that more efficient cars encourage less driving).

Following Greene (2012), we conclude that the evidence in support of the hypothesis that consumers respond in the same way to improved fuel efficiency as to lower fuel prices is

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[19] The test was not applied to the seven (six) of the Type A VKM (PKM) models where fuel efficiency and/or price had been removed from their specifications in Stage 4.

weak, despite the importance of this hypothesis for empirical estimates of the direct rebound effect. Greene speculates that one reason for this result is that the lower running costs of fuel-efficient cars are offset by higher purchase costs, related in the US case to the requirements of CAFE. But this argument rests on a second symmetry hypothesis, namely that consumers respond in the same way to changes in long-run capital costs as to changes in variable costs. This hypothesis also needs to be tested. An alternative explanation is that the consumer response to improved fuel efficiency systematically deviates from the orthodox economic model. If this applies more generally, it has important implications for the determinants and magnitude of rebound effects.

Robustness tests

It is useful to explore the relationship between the aggregate robustness of each model and the estimated size of the rebound effect. This relationship is illustrated in Figure 6 and Figure 7 which include the 28 statistically significant long-run rebound estimates with the expected signs and magnitudes from the 54 VKM models and the 37 estimates from the 54 PKM models. Here, open circles indicate robustness scores using 'Equal Weighting' and shaded circles 'Unequal Weighting'' (Tables 2 and 3). Figure 6 suggests no significant relationship between the estimated size of the rebound effect and model robustness for the VKM models. For the PKM models, we find a statistically significant positive relationship using the unequal weighting results (Kendall's τ at 10% level), but not when using equal weighting.

We also compared the mean robustness scores of different model groups and tested whether these were statistically different (Table 12). For the data used in this paper we found no evidence that static OLS models were more robust than the dynamic models, or that the cointegrated models were more robust than their static OLS counterparts. Using single factor ANOVA F tests, we found evidence that robustness varied with model specification (base, quadratic, asymmetric, reduced), but post-hoc (Bonferroni) comparisons showed that this result derived solely from base models scoring significantly lower than other specifications. In other words, allowing for a saturating responses to income and asymmetric responses to fuel price significantly improved model fit.

Overall, therefore, we find little evidence to suggest that less robust models systematically over or under-estimate the direct rebound effect.

Figure 6 Relationship between the estimated size of the rebound effect and the robustness of the VKM models
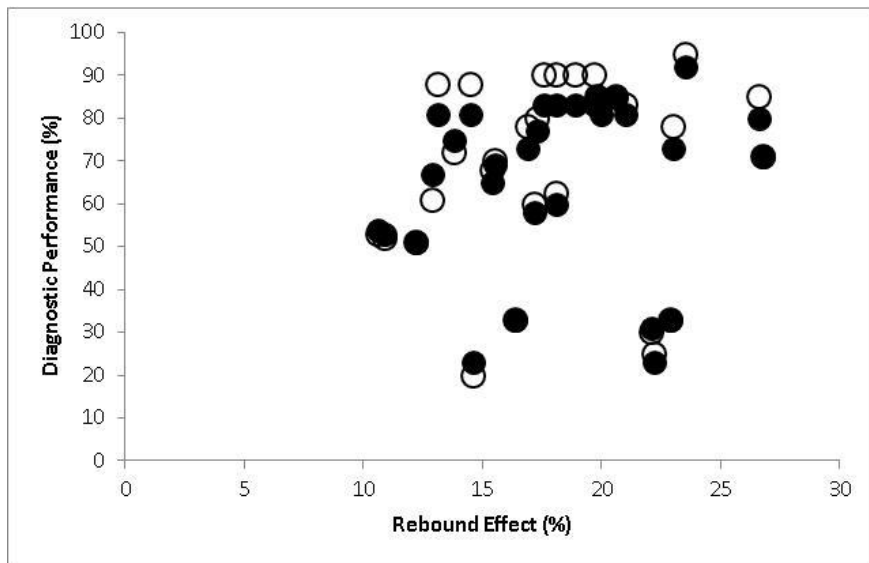

Figure 7 Relationship between the estimated size of the rebound effect and the robustness of the PKM models
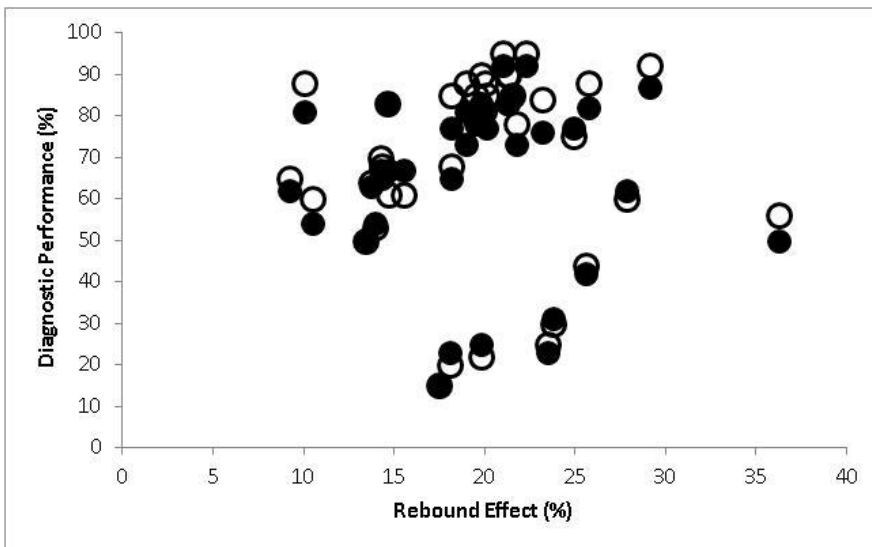
Table 12. Comparing the robustness scores of different model types and specifications

Type	Specification	Nº	Mean Uneq Robustness %	Significantly different?	Mean Equal Robustness %	Significantly different?
Static	All	48	58	NO t = -1.049 P = 0.297	57	NO t = -0.885 P = 0.378
Dynamic	All	48	63		60	
Cointegrated	All	12	86	NO t=1.516 P=0.144	80	NO t=0.099 P=0.922
Static	Optimal	12	80		80	
Static and Dynamic	Base	24	36	YES F=28.122 P=0.000	35	YES F=33.999 P=0.000
Static and Dynamic	Quadratic	24	63		61	
Static and Dynamic	Asymmetric	24	72		69	
Static and Dynamic	Reduced	24	71		70	

5. Conclusions

This study has sought to quantify the long-run direct rebound effect for personal automotive transport in Great Britain over the last 40 years. By estimating a range of models we are able to compare estimates of the rebound effect using different elasticities, different normalisations of the explained variables and different specifications. There are three main conclusions.

First, our data do not support the hypothesis that consumers respond in the same manner to improvements in fuel efficiency as they do to reductions in fuel prices. If changes in fuel efficiency are taken as the appropriate explanatory variable, we find **little** evidence of a long-run direct rebound effect in GB over the last 40 years. However, if changes in either the fuel cost of driving or fuel prices are taken as the appropriate explanatory variable we find **good** evidence of a direct rebound effect, with most statistically significant estimates lying in the range **9% to 36%** with a mean of **~19%**. Using the inverse weighted mean of all estimates gives a slightly lower figure of **~16%.**

These results are consistent with those from US studies and suggest that first: differences in land use patterns, car dependence and travel costs have little influence on the relative size of the rebound effect in these two countries; and second, the common approach of using price rather than efficiency elasticities to estimate the direct rebound effect may potentially lead to biased results.

Second, we find **good** evidence that estimates of rebound effects are larger when distance travelled is normalised to population or the number of adults rather than to the number of drivers. This may be because lower driving costs encourage more people to gain licenses and purchase cars - but to test this properly would require a full structural model. Earlier studies of this topic have not been consistent in their measure of distance travelled which complicates the comparison of results. In addition, we found that the use of passenger rather than vehicle kilometres made little difference to the estimated rebound effect.

Third, we found **some** evidence that the elasticity of distance travelled with respect to fuel cost per mile is greater than the elasticity of distance travelled with respect to fuel prices. This is consistent with theoretical expectations (Equation 2) and demonstrates how the choice of measure for the direct rebound effect can influence the results obtained. If, as Frondel and Vance (2008) argue, the elasticity with respect to fuel prices is to be preferred, then many of the estimates in the literature may overestimate the direct rebound effect for personal automotive travel.

Overall our price elasticity results may be interpreted as suggesting that cheaper car travel has encouraged increased driving in GB over the last 40 years which has eroded around one fifth of the potential fuel savings. While significant, this direct rebound effect has not eliminated the environmental benefits of improved fuel efficiency. However, the overall environmental impact also depends upon: the indirect rebound effects that occur from re-spending the savings in fuel costs on other goods and services (Chitnis et al., 2014); the economy-wide effects that result from changes in prices and incomes (Lecca et al., 2014); and the transformational effects that may result from induced changes in land use patterns and transport systems. These broader effects are harder to quantify, less well understood and usually neglected, but recent research suggests they could be significant (Sorrell, 2007).

Since this is the first study of this type for GB, there is scope for extending the analysis – albeit constrained by the availability and quality of the relevant data. Potential issues to investigate include: addressing the endogeneity of energy efficiency; exploring the importance of additional explanatory variables such as the real cost of public transport; improving the treatment of congestion; investigating the effect of company car taxation and the shift to diesel cars; and exploring whether and how the direct rebound effect has changed over time and/or with income. The last issue is particularly important, since the growing evidence for 'peak car' implies that improvements in vehicle fuel efficiency may have much less impact on distance travelled than in the past. Finally we observe that no previous study

has explored the relationship between the multi-dimensional diagnostic performance of models and the estimated magnitude of coefficients. Although we find little evidence that less robust models systematically misestimate coefficients, this issue is worthy of further investigation.

6. Acknowledgements

Annex 1: Statistically significant rebound estimates

Table A.1 Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel prices ($\eta_{P_E}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Co-integrated	Capita	90	-0.181	18.1	0.058
Static	Capita	83	-0.200	20.0	0.052
Static Reduced	Capita	70	-0.155	15.5	0.028
Co-integrated	Adult	90	-0.197	19.7	0.059
Static	Adult	83	-0.210	21.0	0.052
Static Reduced	Adult	80	-0.173	17.3	0.030
Static Base	Adult	25	-0.222	22.2	0.094
Co-integrated	Driver	88	-0.145	14.5	0.030
Static Reduced	Driver	72	-0.138	13.8	0.027
Static Quadratic	Driver	53	-0.106	10.6	0.036
Static Base	Driver	33	-0.164	16.4	0.038
Mean		*70*	*-0.172*	*17.2*	

Table A.2 Statistically significant estimates of the elasticity of passenger kilometres with respect to fuel prices ($\eta_{P_E}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Co-integrated	Capita	90	-0.213	21.3	0.047
Static Reduced	Capita	85	-0.215	21.5	0.040
Static Asymetrric	Capita	78	-0.190	19	0.047
Static Quadratic	Capita	65	-0.092	9.2	0.042
Static Base	Capita	15	-0.175	17.5	0.064
Static Quadratic	Adult	88	-0.010	10	0.045
Static Asymmetric	Adult	85	-0.201	20.1	0.047
Static Reduced	Adult	60	-0.105	10.5	0.038
Dynamic	Adult	60	-0.278	27.8	0.962
Static Base	Adult	25	-0.235	23.5	0.078
Co-integrated	Driver	68	-0.143	14.3	0.030
Static Quadratic	Driver	64	-0.137	13.7	0.034
Static Reduced	Driver	61	-0.155	15.5	0.027
Static Base	Driver	22	-0.198	19.8	0.037
Mean		*62*		*17.4*	

Table A.3 Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel cost per kilometre ($\eta_{P_S}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard Error
Co-integrated	Capita	90	-0.176	17.6	0.060
Static	Capita	85	-0.198	19.8	0.049
Dynamic	Capita	71	-0.268	26.8	0.825
Static Reduced	Capita	68	-0.154	15.4	0.027
Static Base	Capita	20	-0.146	14.6	0.070
Dynamic	Adult	95	-0.245	24.5	0.540
Co-integrated	Adult	90	-0.189	18.9	0.060
Dynamic	Adult	85	-0.266	26.6	0.815
Static	Adult	85	-0.206	20.6	0.050
Dynamic	Adult	78	-0.230	23.0	0.567
Static Reduced	Adult	78	-0.169	16.9	0.028
Static Base	Adult	30	-0.221	22.1	0.084
Co-integrated	Driver	88	-0.131	13.1	0.035
Static Reduced	Driver	61	-0.129	12.9	0.029
Static	Driver	52	-0.109	10.9	0.037
Static	Driver	51	-0.122	12.2	0.056
Static Base	Driver	33	-0.229	22.9	0.042
Mean		*68*		*18.7*	

Table A.4 Statistically significant estimates of the elasticity of passenger kilometres with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Static Reduced	Capita	95	-0.21	21.0	0.036
Co-integrated	Capita	90	-0.198	19.8	0.044
Static	Capita	88	-0.190	19.0	0.044
Dynamic	Capita	85	-0.182	18.2	0.436
Dynamic	Capita	75	-0.249	24.9	0.583
Dynamic	Capita	68	-0.182	18.2	0.436
Static Base	Capita	20	-0.181	18.1	0.056
Static Reduced	Adult	95	-0.223	22.3	0.036
Dynamic	Adult	92	-0.292	29.2	0.600
Co-integrated	Adult	90	-0.212	21.2	0.044
Static	Adult	88	-0.200	20.0	0.044
Dynamic	Adult	88	-0.258	25.8	0.616
Dynamic	Adult	78	-0.218	21.8	0.461
Static Base	Adult	30	-0.238	23.8	0.068
Dynamic	Driver	85	-0.195	19.5	0.315
Dynamic	Driver	84	-0.232	23.2	0.607
Dynamic	Driver	83	-0.146	14.6	0.363
Co-integrated	Driver	70	-0.142	14.2	0.029
Static Reduced	Driver	61	-0.147	14.7	0.027
Dynamic Base	Driver	56	-0.363	36.3	1.172
Static	Driver	53	-0.139	13.9	0.034
Static	Driver	50	-0.134	13.4	0.052
Static Base	Driver	44	-0.256	25.6	0.039
Mean		*73*		*20.8*	

Annex 2: Approximate formula for variance of long-run elasticity in partial adjustment model

Structure of model:

$$\ln S_t = \beta_0 + \beta_1 \ln Y_t + \beta_2 \ln p_{S_t} + \beta_3 X_t + \beta_4 C_t + \beta_5 S_{t-1} + u_t \qquad \text{A1}$$

Long-run price elasticity: $\eta = \dfrac{\beta_2}{(1-\beta_5)}$

The Delta method involves a Taylor expansion about an arbitrary point. Ignoring second order terms and above, the Taylor formula for expansion of a two variable function $f(x, y)$ is:

$$f(x, y) \approx f(x_0, y_0) + \left[\left.\frac{\partial f}{\partial x}\right|_{x_0, y_0} (x - x_0) + \left.\frac{\partial f}{\partial y}\right|_{x_0, y_0} (y - y_0) \right] + \ldots\ldots \qquad \text{A2}$$

We have: $x = \beta_2; y = \beta_5$. and $f(\beta_2, \beta_5) = \eta = \dfrac{\beta_2}{(1-\beta_5)}$.

Then: $\dfrac{\partial f}{\partial \beta_2} = \dfrac{1}{1-\beta_5}$; $\quad \dfrac{\partial f}{\partial \beta_5} = \dfrac{\beta_2}{(1-\beta_5)^2}$;

Expand around the mean value of the elasticity: $\overline{\eta} = \dfrac{\overline{\beta_2}}{(1-\overline{\beta_5})}$

$$\eta \approx \frac{\overline{\beta_2}}{(1-\overline{\beta_5})} + \left[\frac{1}{1-\overline{\beta_5}}(\beta_2 - \overline{\beta_2}) + \frac{\overline{\beta_2}}{(1-\overline{\beta_5})^2}(\beta_5 - \overline{\beta_5}) \right] + \ldots \qquad \text{A3}$$

Multiply through:

$$\eta \approx \frac{\overline{\beta_2}}{1-\overline{\beta_5}} + \left[\frac{\beta_2}{1-\overline{\beta_5}} - \frac{\overline{\beta_2}}{1-\overline{\beta_5}} + \frac{\overline{\beta_2}\beta_5}{(1-\overline{\beta_5})^2} - \frac{\overline{\beta_2}\overline{\beta_5}}{(1-\overline{\beta_5})^2} \right] + \ldots \qquad \text{A4}$$

Collect terms:

$$\eta \approx \left[\beta_2\left(\frac{1}{1-\overline{\beta_5}}\right) + \beta_5\left(\frac{\overline{\beta_2}}{(1-\overline{\beta_5})^2}\right) + \left(-\frac{\overline{\beta_2}\overline{\beta_5}}{(1-\overline{\beta_5})^2}\right) \right] + \ldots \qquad \text{A5}$$

Let:

$$C = -\frac{\bar{\beta}_2 \bar{\beta}_5}{(1 - \bar{\beta}_5)^2}$$

A6

Then:

$$\eta \approx \beta_2 \left(\frac{1}{1 - \bar{\beta}_5}\right) + \beta_5 \left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^2}\right) + C$$

A7

Take the variance of this:

$$\operatorname{var}[\eta] \approx \operatorname{var}\left[\beta_2 \left(\frac{1}{1 - \bar{\beta}_5}\right) + \beta_5 \left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^2}\right) + C\right]$$

A8

$$\operatorname{var}[\eta] \approx \left(\frac{1}{1 - \bar{\beta}_5}\right)^2 \operatorname{var}(\beta_2) + \left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^2}\right)^2 \operatorname{var}(\beta_5) + 2\operatorname{cov}\left(\left(\frac{1}{1 - \bar{\beta}_5}\right)\beta_2, + \left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^2}\right)\beta_5\right)$$

A9

$$\operatorname{var}[\eta] \approx \left(\frac{1}{1 - \bar{\beta}_5}\right)^2 \operatorname{var}(\beta_2) + \left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^2}\right)^2 \operatorname{var}(\beta_5) + 2\left(\frac{\bar{\beta}_2}{(1 - \bar{\beta}_5)^3}\right)\operatorname{cov}(\beta_2, \beta_5)$$

A10

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Annex 1. *Statistically significant rebound estimates*

Table A.1 Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel prices ($\eta_{P_E}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Co-integrated	Capita	90	-0.181	18.1	0.058
Static Asymmetric	Capita	83	-0.200	20.0	0.052
Static Reduced	Capita	70	-0.155	15.5	0.028
Co-integrated	Adult	90	-0.197	19.7	0.059
Static Asymmetric	Adult	83	-0.210	21.0	0.052
Static Reduced	Adult	80	-0.173	17.3	0.030
Static Base	Adult	25	-0.222	22.2	0.094
Co-integrated	Driver	88	-0.145	14.5	0.030
Static Reduced	Driver	72	-0.138	13.8	0.027
Static Quadratic	Driver	53	-0.106	10.6	0.036
Static Base	Driver	33	-0.164	16.4	0.038
Mean		*70*	*-0.172*	*17.2*	

Table A.2 Statistically significant estimates of the elasticity of passenger kilometres with respect to fuel prices ($\eta_{P_E}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Co-integrated	Capita	90	-0.213	21.3	0.047
Static Reduced	Capita	85	-0.215	21.5	0.040
Static Asymetrric	Capita	78	-0.190	19	0.047
Static Quadratic	Capita	65	-0.092	9.2	0.042
Static Base	Capita	15	-0.175	17.5	0.064
Static Quadratic	Adult	88	-0.010	10	0.045
Static Asymmetric	Adult	85	-0.201	20.1	0.047
Static Reduced	Adult	60	-0.105	10.5	0.038

Dynamic Asymmetric	Adult	60	-0.278	27.8	0.113
Static Base	Adult	25	-0.235	23.5	0.078
Co-integrated	Driver	68	-0.143	14.3	0.030
Static Quadratic	Driver	64	-0.137	13.7	0.034
Static Reduced	Driver	61	-0.155	15.5	0.027
Static Base	Driver	22	-0.198	19.8	0.037
Mean		*62*		*17.4*	

Table A.3 Statistically significant estimates of the elasticity of vehicle kilometres with respect to fuel cost per kilometre ($\eta_{P_S}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard Error
Co-integrated	Capita	90	-0.176	17.6	0.060
Static Asymmetric	Capita	85	-0.198	19.8	0.049
Dynamic Asymmetric	Capita	71	-0.268	26.8	0.103
Static Reduced	Capita	68	-0.154	15.4	0.027
Static Base	Capita	20	-0.146	14.6	0.070
Dynamic Reduced	Adult	95	-0.245	24.5	0.110
Co-integrated	Adult	90	-0.189	18.9	0.060
Dynamic Asymmetric	Adult	85	-0.266	26.6	0.100
Static Asymmetric	Adult	85	-0.206	20.6	0.050
Dynamic Quadratic	Adult	78	-0.230	23.0	0.115
Static Reduced	Adult	78	-0.169	16.9	0.028
Static Base	Adult	30	-0.221	22.1	0.084
Co-integrated	Driver	88	-0.131	13.1	0.035
Static Reduced	Driver	61	-0.129	12.9	0.029
Static Quadratic	Driver	52	-0.109	10.9	0.037
Static Asymmetric	Driver	51	-0.122	12.2	0.056
Static Base	Driver	33	-0.229	22.9	0.042
Mean		*68*		*18.7*	

Table A.4 Statistically significant estimates of the elasticity of passenger kilometres with respect to the fuel cost per kilometre ($\eta_{P_S}(S)$)

Specification	Metric	Robustness score (%)	Elasticity	Rebound effect (%)	Standard error
Static Reduced	Capita	95	-0.21	21.0	0.036
Co-integrated	Capita	90	-0.198	19.8	0.044
Static Asymmetric	Capita	88	-0.190	19.0	0.044
Dynamic Reduced	Capita	85	-0.182	18.2	0.082
Dynamic Asymmetric	Capita	75	-0.249	24.9	0.074
Dynamic Quadratic	Capita	68	-0.182	18.2	0.081
Static Base	Capita	20	-0.181	18.1	0.056
Static Reduced	Adult	95	-0.223	22.3	0.036
Dynamic Reduced	Adult	92	-0.291	29.1	0.104
Co-integrated	Adult	90	-0.212	21.2	0.044
Static Asymmetric	Adult	88	-0.200	20.0	0.044
Dynamic Asymmetric	Adult	88	-0.257	25.7	0.076
Dynamic Quadratic	Adult	78	-0.218	21.8	0.086
Static Base	Adult	30	-0.238	23.8	0.068
Dynamic Reduced	Driver	85	-0.195	19.5	0.046
Dynamic Asymmetric	Driver	84	-0.232	23.2	0.103
Dynamic Quadratic	Driver	83	-0.146	14.6	0.055
Co-integrated	Driver	70	-0.142	14.2	0.029
Static Reduced	Driver	61	-0.147	14.7	0.027
Dynamic Base	Driver	56	-0.363	36.3	0.122
Static Quadratic	Driver	53	-0.139	13.9	0.034
Static Asymmetric	Driver	50	-0.134	13.4	0.052
Static Base	Driver	44	-0.256	25.6	0.039
Mean		*73*		*20.8*	

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